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IoT Ambient Assisted Living: Scalable Analytics Architecture and Flexible Process

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Abstract

With the recent advances in IoT, Ambient Assisted Living (AAL) became an active field that attempts to assist individuals in their Activities of Daily Living (ADL). One researched venue deriving from these advances is how the technology and analytics could benefit the prevention and treatment of chronic diseases in the escalating number of elderly people experiencing health issues. Many architectures are proposed in the literature, but they lack modularity and flexibility for different types of sensors and do not have a way of selecting the appropriate algorithms to perform a given task. In this paper, we propose a four layered and highly modular architecture for health analytics of elderly people. Moreover, we propose a novel automated process for selecting the appropriate algorithms for a task at hand. In the final analysis, we evaluate the approach by implementing part of the architecture on fog nodes and the cloud. Finally, we deploy affordable consumer grade sensors in an apartment in order to move toward the use of the system proposed.

Keywords: IoT; Remote Elderly Monitoring; Smart & Connected Health; Analytics; Ambient Assisted Living;

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1. Introduction

In recent years, there has been a great deal of advancement in the Internet of Things (IoT) due to the increasing number of mobile devices used and the production of useful sensors. In 1999, Kevin Ashton [1] coined the term during a presentation with the goal to collect data automatically and increase efficiency of supply chains. A few years later, it was reintroduced with the idea that ”things” include a controller acting as the ”brain”, sensors, actuators and a network [2]. With the vast amount of data gathered by these ”things”, the concept of big data has to be introduced. Big data means that the data gathered is too big, too fast or too hard [3]. As a result of applying the correct pipelines and processing techniques, we can then perform analytics on the gathered data to try to understand complex correlations in the data. These will be later communicated to inform on the knowledge learnt from the underlying data. Finally, with all the knowledge extracted we can make wiser decisions and act accordingly.

These concepts are used in many fields and domains to solve difficult problems. One of these is related to the healthcare of individuals. The World Health Organization defines eHealth as ”the cost-effective and secure use of information and communications technologies in support of health and health-related fields, including healthcare services, health surveillance, health literature, and health education, knowledge and research” [4]. Another closely related topic is named SmartHealth. The BlueStream Consultancy defines SmartHealth as ”the technology that leads to better diagnostic tools, better treatment for patients, and devices that improve the quality of life for anyone and everyone” [5]. With that in mind, a compelling problem to solve is the prevention and treatment of chronic diseases present in considerable number in the elderly population. Since the 20th century, the number of people that are 65 years old or above with chronic conditions has been rising and will keep growing.

In order to solve the issues surrounding chronic diseases in the elderly population with technologies deployed in their environment, it is imperative to assemble the system in accordance with current healthcare goals and objectives. The concept of using biomarkers to measure a biological state or condition could be useful for this use case. There are 4 biomarkers to think about in our delivery of systems: diagnostic, predictive, prognostic and staging.

The current health care system is focused on treating diseases mainly after it is diagnosed. The collection of data in the environment of elderly people has the capability to aim toward a more proactive way of assessing elders chronic conditions instead of a reactive one. The ”P4 Health Continuum” model was proposed to increase health span by applying the four P’s to healthcare systems: Predictive, Preventive, Personalized and Participatory[6]. The predictive component is used to gather enough information to predict events in order to intervene before it is too late. The preventive element tries to remove the risk factors instead of treating the individual. An example is to identify a risk at the time when it is most reversible. Precise or personalized means to remove the generality in healthcare and customize solutions for the individuals in order to keep them informed and prepared to make better health decisions. Finally, participatory is the idea to engage patients more in the healthcare process and more away front the ”top-down approach”.

Given these points, it is reasonable to believe that ubiquitous computing which encompasses mobile computing and pervasive computing is a relevant technology field that could be accepted by elderly people. One reason is because it focuses on bringing computers in our natural environment without being noticed. Elderly people would be able to see little change in their daily life because the pervasive concepts try to make the computer invisible in the environment while still making it intelligent. The embedded computers are installed in order to gather raw data. This raw data represents pure facts like numbers, text or symbols. From the raw data, it is now possible to retrieve basic information that represents what is actually happening in the environment. It is possible because we have the data in a better context and significance. At the level of information, if we add meaning to what we now know, the information becomes knowledge. By adding insights and strategies we can achieve our goals with a better understanding. This knowledge becomes wisdom when these decisions and judgments are based on a larger social context and your values. This will lead to better decisions. Bernstain [7] explores in detail the Knowledge Hierarchy that was just mentioned.

In the context of elderly activity and biomarkers monitoring, there are many types of possible sensors with the potential to collect essential raw data. For a scalable monitoring solution to be taken seriously, the ease of use and price are incredibly important to take into account.

In this paper, we propose a novel and easy to deploy, affordable sensor and analytics framework to extract knowledge from an elders’ environment by applying the ”P4 Health Continuum” and move toward a more proactive healthcare of individuals. We detail each pillar necessary with the relevant modules to preform the task at hand. Finally, we evaluate the platform by collecting data with our affordable and easy to set up sensors while using the architecture proposed.

The paper is structured as follows. Section 1 presents the introduction. Section 2 describes the related work. Then, section 4 proposes the four layered architecture and section 5 presents the automated algorithm selection process. Next, in section 6 we evaluate the framework by presenting a prototype system application using real sensors and applying our proposed implementation. Lastly, we present concluding remarks and future works in section 7.

2. Related Work

In order to move toward a SmartHealth sensor-based framework that tries to leverage the advantages of pervasive computing and big data, we first have to look to what has been proposed in the literature for generic big data analytics.

Iqbal et al. [8] proposed a big data modelling methodology that has 6 layers. They present them in order: data input layer, data transformation layer, modelling layer, prediction layer, optimization and application layer. Although the architecture proposed enumerates many interesting steps of their big data modelling methodology, they do not go into the details of each layer since they focus more on their universal generative modelling approach called Hierarchical Spatial-Temporal State Machine (HSTSM) which is applied to the layered architecture.

Siow et al. [9] did a whole survey of the IoT and big data analytics that takes into account their utility in creating efficient, effective, and innovative applications and services. They examine the analytics components for health, transport, living, environment and industry domains. The health domain is the most interesting for our tasks. The authors found five main categories of analytics in the literature: descriptive, diagnostic, discovery, predictive, and prescriptive analytics. Moreover, the paper describes the most current data mining techniques such as multi-dimensional data summary, association & correlation, classification, clustering and pattern discovery. Pattern discovery includes anomaly detection. Most of these techniques are undoubtedly part of the proposed architecture in this paper.

One of the applications of data analytics in healthcare information systems is Ambient Assisted Living (AAL). AAL tries to assist the human to accomplish tasks and move toward better aging through the use of hardware, software and artificial intelligence algorithms [10].

Hossain et al. [11] tried to watermark electrocardiogram (ECG) sensed data to ensure integrity. The data is then sent to the cloud for further analysis using machine learning methods in real time.

Hassan et al. [12] propose an architecture that is meant for ambient and biomedical sensors to collect the data of an elderly patient. This architecture is the closest work in comparison to our work. Once collected they fuse it into context states with the goal to predict the health status of a patient in real time using context-awareness techniques. Although the architecture is separated in 4 layers and it aims to put the data in context similar to our architecture, many components are differing in essence or they are not present in one or the other.

Syed et al. [13] were able to recognize 12 physical activities of elderly people with the accuracy of 97.1%. The elder was wearing wearable sensors placed on the subjects left ankle, right arm, and chest. Their novel framework is made of three layers (the perception layer, the integrated cloud layer and the data analytics layer).

Yassine et al. [14] presented another platform for IoT analytics from smart home captured data. They place fog nodes between the smart homes and the cloud in order to push the processing resources required from the cloud toward the edge of the network. They present their three-tier layers as the smart home, the fog node and the cloud. The activity recognition, event detection, behavioural and predictive analytics are performed by the fog and cloud computing systems. The results are then reported to the smart home.

Finally, Raghupathi et al. [15] had explored the major challenges for the three most promising subjects: image, signals, and genomics based analytics. The signal processing workflow proposed in the corresponding section of the paper is especially interesting. At a high level, a large number of wave form data is ingested at high speed. The data is enriched by adding situational and contextual awareness using the history of the patient or other relevant data. After, they perform nonlinear, linear and multi-domain analysis. This layer acts as a feature extraction and signal processing engine to produce insights. Finally, the last layer takes actions based on these insights, such as best action triggers, alarms, clinical decision support and more. The last layer is designed using the diagnostic, predictive and prescriptive analytics concepts.

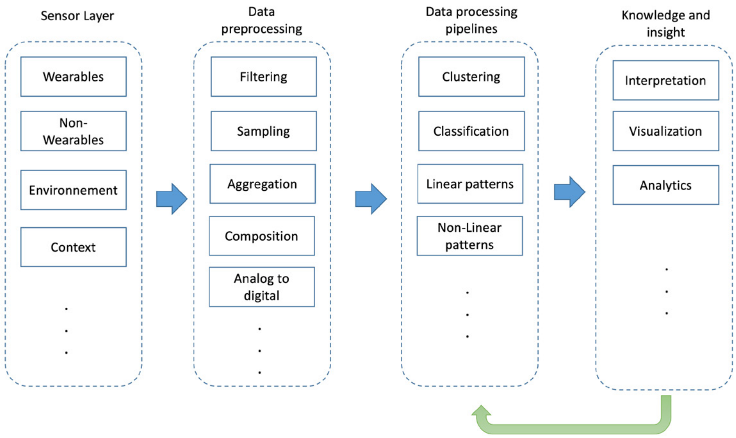

Fig. 1. Data analytics workflow and architecture proposed and separated into four layers.

3. Contribution

While there exists interesting architectures for both big data analytics and smart home analytics such as those described in section 2, they only seem to use a few techniques related to very specific use cases with few options and flexibility. In this paper, we propose a different four layer modular and flexible architecture that can accept many types of sensors. The sensors can be deployed very rapidly in a home of elderly people to monitor their health and ADL's. We introduce a novel automated algorithm selection process for different computing tasks necessary for a SmartHealth analytics. To show the effectiveness of proposed architecture and system, we evaluated it by deploying non-intrusive, consumer grade and long-lasting battery sensors in an apartment. The sensors deployed include: SmartHealth bands, IMU's, multipurpose sensors and BLE beacons.

4. Architecture

In order to perform health analytics for the elderly population, we need to design an architecture that is modular enough to be able to process many types of data such as signals, numerical, environmental, and contextual data. Each of them demand different techniques that are often described in big data analytics surveys [9]. Our architecture shown in figure 1 accepts these as inputs in the first layer. This layer is also known as the sensor layer. Next, this plain data received from each sensor is coming through at a fast rate and in enormous amounts. It is way too expensive and costly to take the sensor data and pass it directly to our knowledge extraction algorithms. Thus, we go through a data preprocessing layer, which uses many techniques to reduce the amount of unnecessary data while keeping the most significant one. The layer is also parametrized to help get the type of data that you need and at which rate. The third layer accommodates the data processing pipelines available to extract information from the preprocessed data. Our last layer is the knowledge and insight layer. We use different modules to give the user the ability to make smarter decisions. We introduce modules for interpretation, prediction, visualization and analytics. It is important to note that the fourth and last layer is closely connected with the third layer because the knowledge and insights collected can be returned back through the data processing pipelines to retrieve even more insights or create a continuous learning cycle.

Layer 1: Sensing

The first layer to implement in our architecture is the sensor layer which is used to capture the raw data from the sensors deployed in the elders' environment. These sensors can be of many types. We identify at least four types: wearables, non-wearable, environmental, and contextual. These sensor types are not exclusive to only one category. They can belong into more than one type at a time.

Wearables: The wearable component is encapsulating the sensors that may be placed on the body of the monitored individual. Some examples include PPG and ECG smart bands that retrieve physiological information. Recently, such smart bands have been successful in many studies. One very famous example is the Apple Heart Study (AHS) [16]. Another available information gathering sensor through wearables is the IMU that retrieves motion data. This inertial measurement unit is an umbrella sensor that often gathers data from accelerometer, gyroscope and magnetometer sensors. Finally, we can find the blood oxygen concentration (SpO2). These sensors are introduced in more and more innovative and affordable wearables like smart clothing, belts, rings and even shoes.

Non-Wearables: Non-wearable sensors are the sensors that can retrieve information on the individuals with or without physical contact. Such sensor category includes 2D cameras, lidar cameras, smart scales, mattress sleep assessment sensors, localization beacons, etc. They are interesting sensors to include because of the added value brought without having to be worn at all times.

Environnemental: It is beneficial for a health system to make use of environmental sensors because they can be placed and used without being intrusive. Such sensors usually need a way to communicate with a node in order to make use of what is sensed. We find that we can place ambient temperature, contact, tilt, vibration and audio sensors in the environment to gather its information and state.

Context-Aware: The idea of context-aware sensors is that we are able to retrieve spatio-temporal information from them. We can find these when there are spatial and temporal dependencies between readings. For instance, a wearable accelerometer sensor allows us to get the the spatial movement of the device often associated with a timestamp that determines when the reading was sampled. As we can see here, an accelerometer falls into both the wearable and context-aware categories.

Layer 2: Data Preprocessing

The second layer of the architecture is the data preprocessing layer. With a vast amounts of incoming data, it is essential to build an efficient first data collection funnel. One reason is because the data collected comes in at a fast rate and with redundancies that can be eliminated if appropriate filtering techniques are used. This funnel helps reducing the amount of processing necessary to extract knowledge in the upper layers. Finally, each modular component can get its own parameterization in order to produce a set of meaningful and versatile metrics to experiment with.

Filtering: The filtering component is used to maximize the amount of useful data and minimize the redundancies in incoming data. It is also used to remove noise in the data [17]. Filtering is a form of lossy compression, which means that it reduces the size of the data, while erasing some of it at the same time. For instance, the Fourier transform is a popular mathematical transformation to filter out different frequencies that compose a signal. Following the Fourier transform rules permits us to recreate any signal by the sum of its sinusoids. This frequency information is crucial to extract the most important information in the signals. Another useful filter for the accelerometer is the bandpass filter.

Sampling: Digital sampling aims at listening to an analog continuous-time signal, quantize and discretize it in time, then store it in memory. An important concept to take into account when sampling is known as the Nyquist frequency. The Nyquist frequency is half of the given sampling rate.

Aggregation: In order to minimize the size of data storage necessary, aggregation can be used to take a table of data and highlight useful statistics from it. These statistics, such as mean, standard deviation and others, can then be used to perform analytics in the upper layers of our architecture [17].

Interpolation: Interpolation is a strategy that allows us to estimate what should be between data points when the signal is already sampled. Normalizing signals that are sampled unevenly is a useful way to utilize interpolation. Additionally, it can be used to compare two signals sampled at different rates. You can interpolate a signal to make use of an other sampling rate.

Resampling: If we have a certain discrete signal, resampling means that we need to change the sampling rate for that signal.

Composition: In our architecture, the data is coming from numerous sensors. Often, it also has different data types coming from the same sensor. As a result, we can combine these using composition to produce new augmented data. A simple example of composition is seen when we combine temperature and humidity to obtain the humidex index using a chart.

Analog to digital: An analog-to-digital converter (ADC) is used when an analog continuous-time signal needs to be encoded to a discrete digital numbers format. The analog signal is often a voltage.

Layer 3 : Data Processing Pipelines

This layer is focused on taking the preprocessed data from the previous layer and use it to recognize important patterns or classifying the data such as clustering, classification, linear and non-linear patterns etc.

Clustering: The goal of clustering is to group the data collected into classes without any labels attached to these groups. Clustering techniques are unsupervised, which means that there is no known true labels for the model training. Moreover, we do not know how many clusters will be formed from the input data. Wong [18] defines it formally as "given a set of data instances, a data clustering method is expected to divide the set of data instances into the subsets which maximize the intra-subset similarity and inter-subset dissimilarity, where a similarity measure is defined beforehand". They also present us with a survey of the different paradigms used in the field. Among them are partitional, hierarchical, density-based, grid-based, correlation, spectral, gravitational, herd, and other clustering paradigms.

Classification: When instances of data have a corresponding true class label with them, we are now into the field of supervised learning [19]. Classification algorithms constitute one category of supervised learning. The other one being regression algorithms. For classification problems, we can only classify outputs as unordered discrete values. We can split the classification algorithms into a few subcategories: logic based algorithms, perceptron-based techniques, statistical learning algorithms and support vector machines.

Linear Patterns: The linear patterns are used to discover patterns that evolve linearly. For instance, a continuous linear trend in increasing or decreasing values will appear as a straight line across the data.

Non-Linear Patterns: When the independent variables are not showing a linear pattern, we can try to fit the data to a complex nonlinear function.

Layer 4: Knowledge and Insight

For our fourth layer, we find a layer that is aimed toward making use of all the information we have accumulated so far. At this level, we can present the data to a user, interpret it, predict future outcomes and perform analytics.

Interpretation: In the interpretation component of the architecture, we define rules or patterns that are meant to characterize the data and give it a signification that is in relation to the domain of the data. The question that we are asking is: What does the information retreived actually mean in a specific domain?

Visualization: The visualization component is aiming to provide a graphical view and presentation of the data. It is helpful to create these to let decision makers understand complex ideas and observe new structures or patterns. Letting the user interact with the visualizations helps to grasp more detail out of the underlying data [20]. The ultimate goal here is to show information and let the viewer try to extract knowledge out of it. To name a few of these methods as examples, we can use: histograms, line charts, tables, pie charts, bar charts, scatter plots, bubble plots, area charts, flow charts, Venn diagrams, data flow diagrams, time lines, multiple data series, entity relationship diagrams, cone trees, semantic networks, tree maps and parallel coordinates, etc.

Analytics: The analytics in this layer play a major role in attempting to gain knowledge from the information. We mentioned and described the five types of analytics in section 2. These were: descriptive, diagnostic, discovery, predictive, and prescriptive analytics [9]. As an example, predictive analytics is about making use of current and historical data, apply statistics and modeling methods to it, and anticipate what the future may become. Predictive analytics is closely related but distinct from many quantitative approaches: statistics, forecasting, optimization, discrete event simulation, applied probability, data mining and analytical mathematical modeling [21].

5. Automated Algorithm Selection

In the previous section, we have described a four layered architecture with the goal to achieve SmartHealth monitoring of elderly people. With the large amount of data coming in at a fast rate, the complexity of knowing which components to use and when becomes increasingly difficult to figure out. For this reason, we are proposing a flow process to help with the selection of appropriate algorithms in order to get optimal results from our architecture.

The flow proposed and displayed in figure 2 begins on the left side with four inputs sent to the gear symbol, which represents the Matching Engine component of the process. Starting from the top of the three inputs represented in blue, the profiles of algorithms component is acting as a repository of metadata, information, algorithms and tools available

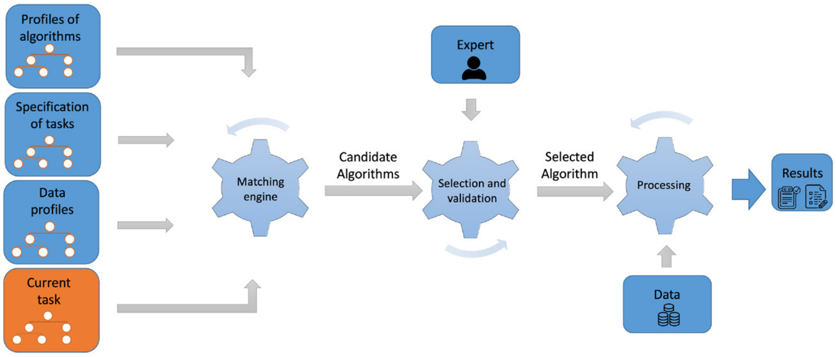

Fig. 2. Process of algorithm selection for a specific task.

and pre-assembled. Secondly, the specification of tasks component is a standardized way of defining tasks that are accessible to execute. Third, the data profiles component represents a standardized description of the data. Ultimately, in orange, we find the task at hand that we would like to perform. It is marked in orange because it is a dynamic input to our matching engine. With the three repositories accessible and the current task at hand, the matching engine has the purpose of automatically selecting a list of candidate algorithms. Once the list of candidate algorithms is produced, another flow component handles the selection and validation of the final algorithm. At this level, an expert (human or program) could make the final choice of the algorithm. The selected algorithm is going to be treating the input data from our previous architecture, to produce our results.

6. Evaluation

All things considered, it is crucial to deploy this architecture in the real world in order to prove its effectiveness. We implemented parts of the architecture in order to be able to start collecting data from affordable consumer grade sensors. We started by finding the sensors and figure how they communicate the data with the goal to implement the correct components in the sensing layer of the architecture. Moreover, depending on the sensor data type, the subsequent layer components are impacted.

Sensors

When looking for sensors to recognize the ADL's of elderly people, we look for sensors that belong and conform to the sensing layer described earlier. Additionally, it is beneficial to look for sensors that are not intrusive, affordable and accessible. The reason is that, for the platform to be easily and quickly deployed in their environment, off-the-shelf products are a perfect fit by being ready to use and optimized for commercial use [22].

That being said, for the wearables component of the sensing layer, the first wearable item we picked is the Mi Band. It is one of the most affordable of the smart bands at an approximated $50 USD. Also, this band benefits from a battery life of up to 20 days. It has a 3-axis accelerometer, 3-axis gyroscope, PPG heart rate sensor and capacitive proximity sensor. In the same wearables category, we added a MetaMotionC (MMC) from the MbientLab company. The MMC has many useful sensors included in the device such as: 6-axis accelerometer and gyroscope, 3-axis magnetometer, ambient temperature, barometer, pressure, altimeter and ambient light. These last two devices connect through a Bluetooth connection to a mobile application.

Next, we use BLE beacons from Estimote alongside a mobile application. These sensors are classified as environmental sensors. The BLE beacons emit iBeacon packets continuously for a solid three years. The mobile phone can listen to these packets and use the signal strength to calculate the proximity or distance from a beacon deployed in the environment of the elder. Also in this category, we can connect the popular Samsung SmartThings environmental sensors. The difference here is that they communicate via Zigbee. For that reason, we connected them to a hub such as a Raspberry Pi with a ZigBee USB Gateway running the Home Assistant software. We experimented with the

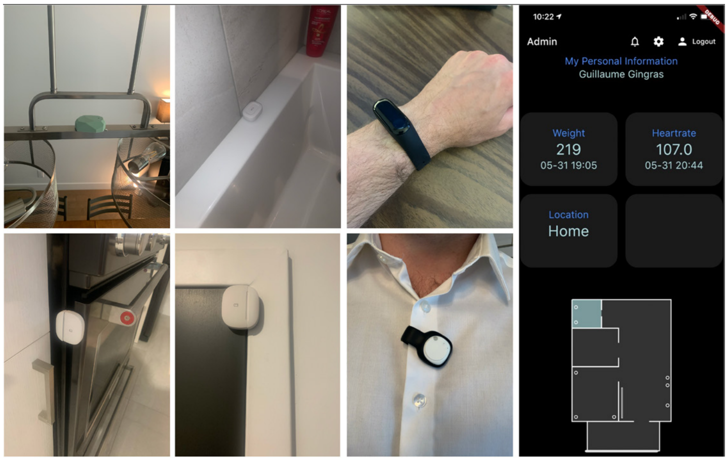

Fig. 3. Our choice of different types of sensors deployed in an apartment and connected to a mobile application.

multipurpose sensor, water-leak sensor and button. Each of them emits changes in ambient temperature which can be useful when placed near appliances that generate heat. The multipurpose sensor emits changes in vibration, tilt and contact with its magnet. The water leak sensor detects water that touches its sensor. Finally, the button emits a signal when pressed.

For non-wearable sensors, we have a Fitbit Aria 2 smart scale that connects to the Wi-Fi of the apartment. We can easily retrieve data from the Fitbit database using their api. This scale is able to measure our weight and digitally sends the data to the cloud associated with the linked account of the scale.

Finally, in the category of contextual sensing, we can use the mobile application of the user to know if the user is home or not. We can even use the mobile application GPS module to get data about where they are exactly and at which speed they are travelling. This spatiotemporal information has the potential to put other data sources in a better context.

Implementation

We briefly mentioned above that we deployed the architecture in a real world setting inside a small apartment. When describing the apartment, we virtually separated the area to 8 regions. These regions include a kitchen, bathroom, bedroom, living room, dining area, office, entrance and balcony.

The sensors mentioned above are using different communication protocols. The two protocols that are the most often used in our implementation are Bluetooth and ZigBee. We also assume that the elder has a smartphone. It is used to to keep a connection with the Bluetooth devices. It is also used to retrieve GPS coordinates when outdoor. For these reasons, we decided to deploy part of the implementation using a mobile application. The mobile application is built using Google's Flutter framework. We use an in-memory relational database to capture the continuous streaming data coming from the accelerometer, Bluetooth BLE beacon messages, PPG smart band heart rate, GPS and place mark updates. There are two ways for moving forward from this point. Locally, we can now apply all three layers left: data preprocessing, data processing pipelines and knowledge and insight. An example of what we are able to extract is entering and exiting regions in the apartment by filtering the BLE Bluetooth received packets. In contrast, we can send the data to a cloud database. We are using Google's Firebase Firestore document based database. It is inefficient to send all the data directly to the cloud from the local database because not all of the data is relevant or of equal importance. To that end, a lot of our second layer (data preprocessing) is implemented on the mobile application. Once preprocessed, we send the data to the cloud database where the last two layers of our architecture can be implemented as well.

At the same time, we have the ZigBee sensors which are deployed in the vicinity of important areas in the apartment. To receive the changes in states from them, we can set up rules to send HTTP Post requests to our web server inside the automation and configuration YAML files in the Home Assistant. In our implementation, we send each state change directly to the Firebase Firestore cloud functions that listens for these requests. Similarly to the mobile phone, it would be possible to implement all the layers locally on the Raspberry Pi and the last three layers on the cloud.

7. Conclusions and Future Work

In this paper, we proposed a modular four layer architecture to perform SmartHealth analytics using the different components needed when working with multiple types of data sources. These inputs form our sensing layer. The subsequent layers represent data preprocessing, data processing pipelines and knowledge and insight layers. Furthermore, we presented an automated algorithm selection process to pick the best algorithm for a specific task at hand. To evaluate the effectiveness of our approach, we deployed a set of sensors preliminary version of an implementation of the architecture in an apartment. The sensors vary in type and the architecture is a base to build upon for future works. To further solidify and validate the methods proposed, we plan to continue implementing more of the architecture, such as adding more filtering methods, apply more machine learning and complete the full cycle of life of data. Finally, we still need to apply our automated selection process to it and distribute the solution in a pilot project in the region of Quebec, Canada. The objective is to monitor between eight and ten rural seniors for health issues and their ADL's.

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